

Towards a Context-Aware Adaptable Services Framework with Applications in Elderly Care

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Abstract. In this paper, we present our latest work in the design and implementation of a context-aware probabilistic model for endowing service robots with the ability to automatically adapt to different contextual conditions.

Our system relies on Bayesian techniques to, given a past history of interactions and the current context the user and the robot are immersed in, estimate the user’s expectation at that given point in time.

Given this ability, a service robot should be able to predict its user’s needs and increase the quality and acceptance of its services.

The system has been successfully tested in simulation, and we believe that its application in the field of Ambient Assisted Living will contribute to an improved user experience.

Keywords: Adaptable Services, Ambient Assisted Living, Social Robotics, Companion Robots

1 Introduction

Population ageing is a growing concern. As the so-called “baby-boomers” age, they drive the general population’s tendency to grow older, creating a political, humanitarian and social problem all over the developed world.

A recent study by Eurostat [1] indicates that the median age across Europe has been rising in a sustained manner, and postulate that this rise will continue for years to come. It is projected that, by 2080, 28.7% of the European Union’s population will be over 65 years old [1].

The technological revolution of the twentieth century has deeply changed the lives of virtually every single inhabitant of the developed world. A glaring exception, however, are the elderly, who remain generally incapable of keeping up with the latest technological developments. We argue that this issue is due

This work was developed in the context of the GrowMeUp project, funded by the European Union’s Horizon 2020 Research and Innovation Programme - Societal Challenge 1 (DG CONNECT/H) under grant agreement N  643647.

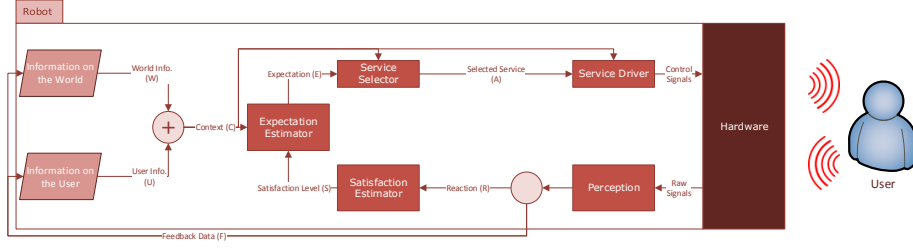


Fig. 1. A simplified pictorial description of the system's operation.

to a mismatch between the interfaces that are developed and the user's ability to adapt to them, *i.e.* that the use of interfaces that allow for a more natural interaction should increase the level of acceptance of technology by the elderly portion of the population.

The GrowMeUp Project, described in detail in [2], is currently developing a solution that aims at increasing the quality of life of elderly citizens that live alone via a robotic platform and a cloud-based infrastructure that will allow the users to remain connected both to their caregivers and to their social circles.

This solution will allow the users to live independently for a longer time, delaying the need for full-time care and for the removal of the person from their preferred environment, and thus increasing the quality of life of the users. This solution will bring together three very important aspects of the life of the user: the user themselves, their caregivers and their social circles.

Additionally, the system will perform several functions, such as reminding the user to take their medication, or estimating their emotional status and initiating interaction with the intention of mitigating any feelings of sadness or loneliness. The system will attempt to elicit empathy from the user, and to become, in the perspective of the user, a real addition to their social circle and, ideally, a companion.

Building on the GrowMeUp system, we have developed a rationale and a preliminary system that aims at promoting the naturalness of the interaction between the user and the robotic platform by estimating what action the user expects the robot to perform and by using an estimate of the user's degree of satisfaction to measure how pertinent the performed action was.

In this work, we briefly present our solution and the latest challenges and procedures pertaining to the testing of our solution with real users.

2 Improving Human-Robot Interaction by Estimating the User's Expectation

Our solution, pictorially described in Fig. 1, operates essentially by relating the current contextual data with the past interactions the robot has had with the user.

Contextual data is essentially composed of two different classes of data: *information on the user*, comprising data such as what action the user is performing and what emotion they are exhibiting, and *information on the world*, such as the current time of day, and the current location of the user and of the robot.

Every time our system is triggered, by the user or some other component of the larger system, it uses contextual information and past interactions to estimate the user's current *expectation*, *i.e.* the action that the user wants the robot to perform, effectively producing an estimation of what *service* the user currently expects the robot to execute.

Once an action is selected, the system actuates on the world and measures the user's *reaction*, constituted by features such as the action being performed by the user and their emotional state, which is then used to estimate the user's *satisfaction*. This metric will then be used to train the Bayesian models the system operates on. As time goes on, and through repeated interactions, the system will build an increasingly-accurate probabilistic model of the user's expectations and how they relate to the environment the user and the robot are immersed in.

We have implemented our model using, as mentioned, Bayesian methods akin to Naive Bayes Classifiers. Essentially, the Satisfaction Estimator calculates the value

$$\xi = P(S|R) \propto P(R|S)P(S), \quad (1)$$

which is calculated assuming a uniform distribution for $P(S)$ and a distribution for $P(R|S)$ which is learned during training, and where ξ represents our estimation of the user's level of satisfaction.

Similarly, the Expectation Estimator calculates the probability

$$P(\chi|\xi, C) \propto P(\chi)P(\xi, C|\chi), \quad (2)$$

where χ is the set of all possible actions the robot can perform.

Typically, this node is not trained, and is expected to learn during execution, by updating the $P(\xi, C|\chi)$ term after every interaction. Nevertheless, this node can be trained by manipulating the aforementioned term.

3 Implementation and Testing: Preliminary Results and Future Test Procedures

Our solution was tested in a simulated scenario. The results of those tests are partly pictured in Fig. 2 and briefly described in the following paragraphs.

The implementation, using a fully trained Satisfaction Estimator and a non-trained Expectation Estimator, was presented with a series of contextual situations, and used to estimate the user's expectation. Given this estimation, our test driver would then generate a reaction which was randomly drawn from the distributions that characterized the user's reaction given their satisfaction status. This reaction was then processed by the Satisfaction Estimator.

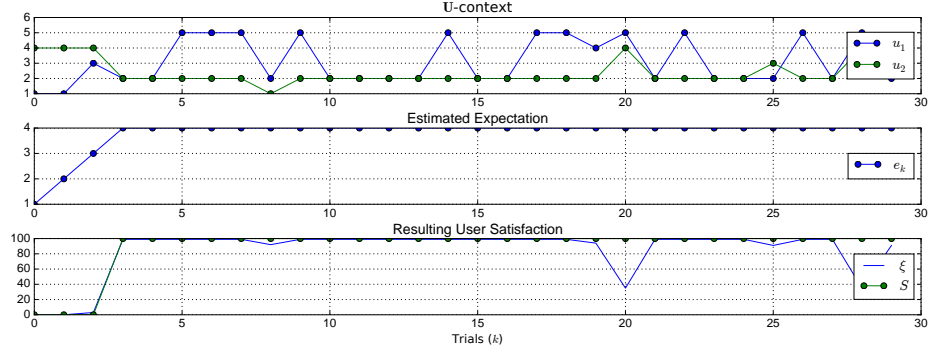


Fig. 2. The results obtained in one of the simulated tests we performed.

We have observed that, after a relatively short period where the system tends to iterate through all possible expectations, effectively searching for the correct expectation, the system is able to consistently elicit a positive response from the simulated user, even when the randomly-generated reaction led the Satisfaction Estimator into error. These tests have shown that the model is both valid and robust.

Following these promising simulation results, we are aiming to implement a working, fully operational prototype of a service-rendering system based on our probabilistic model using the GrowMu robot, pictured in Fig. 4.

We have decided that, for the first real implementation of our system, we will rely on explicit interaction, by directly asking the person if the estimated expectation corresponds to reality, thus determining the degree of satisfaction of the user, as described in Fig. 3. This solution constitutes a trade-off between the functionality we wish to implement, which should not rely solely on explicit interaction, and the current availability of reliable action recognition and emotion detection techniques. Naturally, we will further investigate the possibility of including several signal processing techniques with the goal of improving the system, and also of improving our system in order to be able to deal with information that carries more uncertainty than initially desired.

For this first version, the test procedure is as follows: as before, the system starts untrained. Then, while cycling through various contextual states, attempts to estimate the user's expectation. These trials will allow the system to learn the preferences of the user, relating them to the environment they share. Having completed the training phase, the system should be able to, given the current context, determine the service that the user expects the robot to perform.

This test, albeit exceedingly simple, should allow us to validate the results obtained in simulated scenarios, pertaining to the performance of our mathematical models, and also gather some initial data on the response of real users to the behavior of the system.

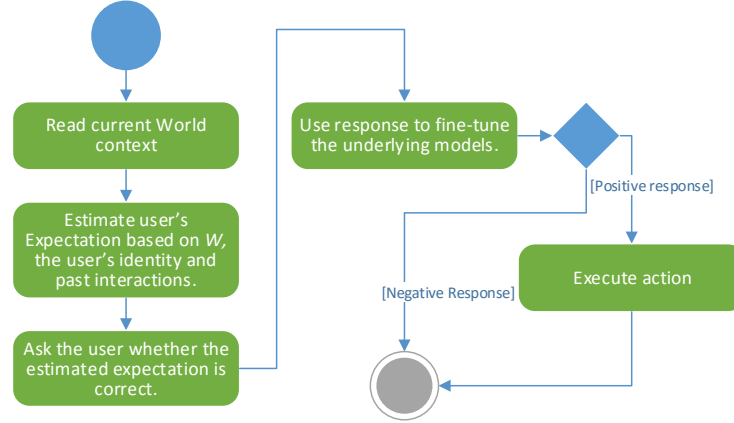


Fig. 3. The UML activity diagram that serves as a guide for the implementation of our first, basic test scenario.

3.1 Person Profiles and Multi-User Scenarios

The model we have presented is not tailored for use with multiple users. However, as an addition to previous work, we are preparing an extension of our system that is able to estimate the user's expectation given also the user's identity, as shown in Fig. 3.

This extension follows from the following rationale. Our model constructs a probabilistic distribution that relates the user's preferences to the context in which the interaction takes place and, given a training phase, that relates the user's reaction to their level of satisfaction with the service that was rendered.

However, it can be easily proved that, even at such a simplistic level, different people will exhibit different preferences (essentially $P(E|C, I)$, where I is the user's identity), and a different relationship between their level of satisfaction and the reaction they produce (similarly, $P(S|R)$).

This fact may help us, in the future, to endow our system with the ability to, not only adapt to various different users, but also to construct a set of *person profiles* that can then be used to, from a fairly reduced amount of data, deduce the person's reaction-satisfaction and context-expectation relationships in a manner that is more robust and intuitive than the current solution, that involves a training phase and an exploratory phase of execution during which satisfaction is not guaranteed.

4 Conclusions

In this paper, we have briefly presented a preliminary report regarding our current work a probabilistic model for promoting adaptability in service-rendering scenarios.



Fig. 4. A picture of a user interacting with the robot.

We have presented our motivations, a short description of the current status of our work, as well as a description of the current issues we are facing, the possible solutions we may apply and the testing methodology we will apply during the next few weeks.

We believe that, given the results obtained in simulated testing, the application of our technique within the project and, thus, within the field of Ambient Assisted Living, could constitute a significant contribution towards the simplification and “naturalization” of elderly-centered human-machine interfaces. By effectively *guessing* what the user desires at a given moment, our technique endows the robot with the ability to provide services to any given person, be they usually able to deal with technology or not.

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